

Job Descriptions Keyword Extraction using Attention based Deep Learning Models with BERT

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Abstract—In this paper, we focus on creating a keywords extractor especially for a given job description job-related text corpus for better search engine optimization using attention based deep learning techniques. Millions of jobs are posted but most of them end up not being located due to improper SEO and keyword management. We aim to make this as easy to use as possible and allow us to use this for a large number of job descriptions very easily. We also make use of these algorithms to screen or get insights from large number of resumes, summarize and create keywords for a general piece of text or scientific articles. We also investigate the modeling power of BERT (Bidirectional Encoder Representations from Transformers) for the task of keyword extraction from job descriptions. We further validate our results by providing a fully-functional API and testing out the model with real-time job descriptions.

Index Terms—keyword extractor, job descriptions, SEO, attention mechanism, BERT, screening, summarization

I. INTRODUCTION

A valuable concept for searching and categorizing job descriptions is the keyword, a short set of words (one or few) which represent concepts and offer a compact document's content representation. Perfectly, keywords are representing in compressed form the important document content [1].

Extracting keywords from a general text is a difficult activity as we need some idea of how these keywords are related to the paragraph and if they are trending for better Search Engine Optimization (SEO) [2, 3]. We aim to solve this problem using a state of the art algorithm which once trained can be used for multiple purposes such as Resume Screening, Keywords for Job Description, etc. SEO can heavily impact a company's ranking on search engines [4, 5].

We propose a Machine Learning system that can analyze a text corpus from a job description and output some suggested keywords which could be applied specifically using topic modelling techniques [6]. One of the main objectives is to

facilitate easy, efficient and meaningful job search. Millions of jobs are posted but are usually not accessible due to improper SEO. It is also practically impossible to manually list down keywords for a given job description when they are in quantity. The proposed system is more flexible and versatile than the traditional manual way of doing so. The Scope is not just restricted to SEO, once the algorithm is developed, it can be used for a wide range of applications including screening resumes, shortlisting perfect candidates, suggesting changes, automatically adding tags (for better SEO) and filtering job listings etc [7].

We automate the process of extracting relative keywords from job descriptions allowing for job postings to get better relevant SEO rankings. We use the same model and concepts and apply them to many more problem statements like automating resume checking, adding tags for a given block of text, etc. Most organizations rely on search engines algorithms to get their job postings listed or manually put keywords to rank it higher which is pretty time consuming. We automate this for the organizations so that it can be directly integrated with their existing system with little or no changes.

We also aim to make the process hassle-free and very easy to implement by providing a simple to use REST API and gRPC servers which can allow this to be integrated into existing system very easily by organizations. To further make this easily accessible by administrators and HRs, we also provide them with a UI where they could simply paste their job descriptions and generate the relevant keywords making the process a lot easier for them and save human efforts as well.

Several neural models comprised of pre-trained word as task agnostic embedding layer EL and neural architecture being task-specific were proposed for the keyword as original or key-phrase extraction problem [8–11]¹ whereas such models

¹Due to limited space, we do not list all of the existing works here, please refer to the surveys [12, 13] for more related papers.

improvement measured through the correctness or score of F1 has arrived to a bottleneck. One of the reasons in which the EL as task-agnostic is typically of layer linearly prepared along with Word2Vec [14] or GloVe [15], just offers context-independent word-level characteristics that is inadequate to capture the dependencies as complex semantic in such sentence.

In this paper we also investigate the modeling power of BERT (Bidirectional Encoder Representations from Transformers), one of the most popular pre-trained language model with Transformers [16], on the task of keyword extraction from job descriptions. We also make comparisons between BERT-based models and those keeping BERT component fixed. We find out that the BERT-based models perform a lot better than those trained keeping BERT component fixed for the downstream tasks. So, we perform task-specific fine-tuning allowing us to make the best use of the BERT strengths for performance improvement [17]

We also propose a way to keep updating the model behind this in real-time through user feedback. We further also provide ways in which this model and data apart from adding keywords to job descriptions can also be used to derive insights from resumes or automatically add tags for a certain block of text. When performing this on a large number of similar documents like resumes or scientific articles we also try to extract keywords from particular sections to prevent analyzing the full text of an article requires more disk space and the analysis needs more computational capacity [18]. Apart from this, with enough information we could also use these models and data to perform summarization of articles [19], job descriptions and general text too [20].

The remainder of this article is organized as follows. In II section the system design and the model architecture is presented. In III section the data used for this paper and our collection methods are presented. The IV section experimental results of the model and the API are presented. The V section concludes the article and gives future works.

II. SYSTEM DESIGN AND MODELS

The main purpose of the proposed system is to generate keywords from a corpus of text and to also eliminate the physical keywords extraction and other hassles and make the system completely hassle-free. The architecture as overall for the adopted model is represented in Fig. 1.

A. BERT as an embedding layer

We first perform word embedding of the job description text to represent them as low-dimensional vectors. A popular implementation of embeddings word are the Word2Vec [14], GloVe [15], and the models of fastText [21]. However, a major problem we face with these traditional models or ELs is that we get a single context-independent representation for each token which results in losing the correct sense of the token. This also proves to be highly inadequate to capture the dependencies as complex semantic in a sentence which would be very much needed in this use case. To preserve the context

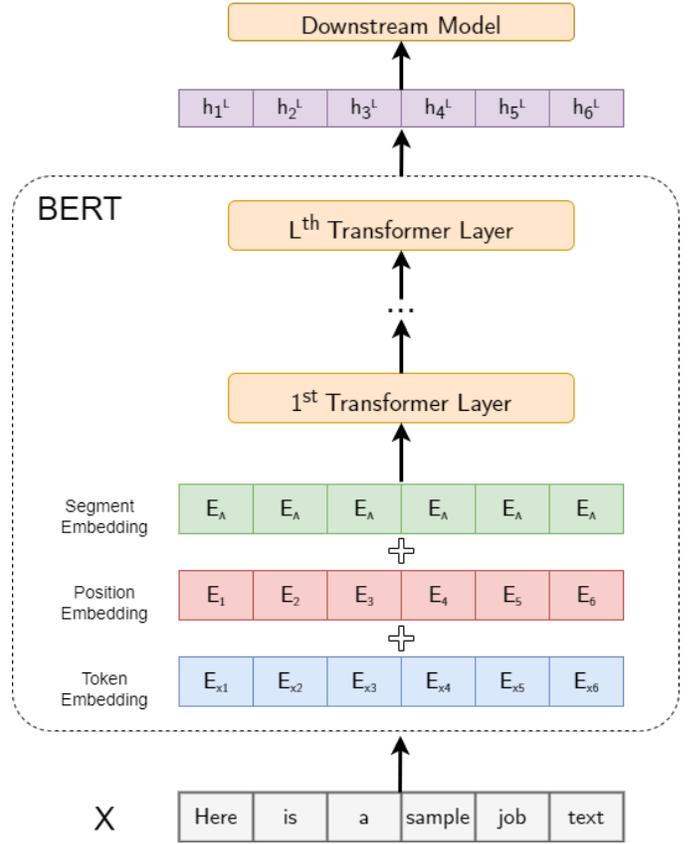


Fig. 1. Topic scores for an example job description.

in which the token is used and perform embedding in that sense we make use of the BERT model [22].

The model architecture of BERT is based on a Transformer encoder of multiple layers that was applied originally through Vaswani et al. [23]. Devlin et al. [22] presented the BERT Transformer according to the utilization of self-attention as bidirectional. Such a mechanism as bidirectional eliminates the limitations that self-attention can just integrate the one side context: right or left. BERT makes use of Transformer which eschews recurrence and is based solely on attention mechanisms which have become an integral part [24] which learns relations as contextual between text sub-words or words [23]. In its vanilla form, the Transformer includes two separate mechanisms, an encoder which reads the input of text and a decoder that creates task prediction.

Compared to the traditional layers embedded that just offers representation as context-independent being single for every token, the BERT EL considers the sentence as input and figures the representations of token-level utilizing the data from the whole sentence [25]. Given the input token sequence $x = \{x_1, \dots, x_T\}$ of length T , we firstly employ the BERT component with L transformer layers to calculate the corresponding contextualized representations $H^L = \{h_1^L, \dots, h_T^L\}$ for the input tokens. Specifically, the representations $H^l = \{h_1^l, \dots, h_t^l\}$ at the l -th for $l \in [1, L]$ layer are figured as

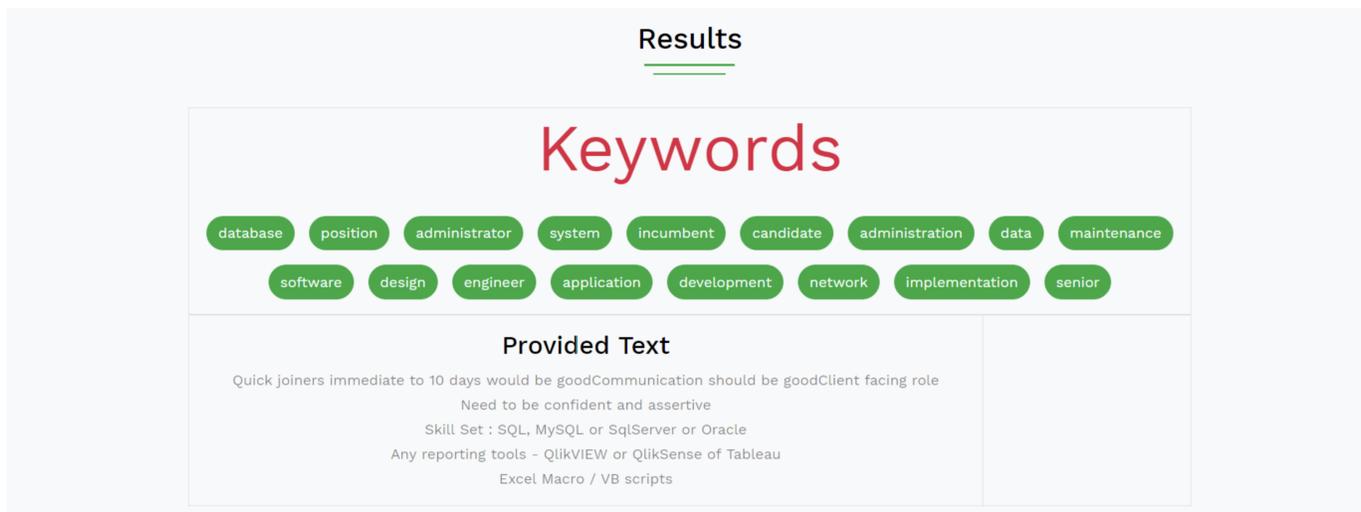


Fig. 3. Example of output from the model API.

freely and also use web content extraction for extracting less structured data [40], using combination of density sum shown by Sun et al. [41] and CSS features.

We then label this data using some crowd sourcing techniques [42], to make sure that users have truthfully submitted data we make use of the techniques mentioned by Zhao et al. [43] and also make sure to control the quality of data [44] we gather by crowd sourcing it. We further make sure to follow some additional tips and best practices that are crucial to the success of any project that uses crowd sourced data mentioned by Vaughan et al. [45].

We originally started developing and implementing the ideas on "Online Job Postings" data set [46] but soon found the data to not be enough and outdated so we also made use of scraping approaches to gather data apart of this.

IV. EXPERIMENTAL RESULTS

As we mention earlier we use the pre-trained "bert-base-uncased" model by HuggingFace Transformers [47] where the number of transformer layers we use is $L = 32$ and the hidden size dim is 1024.

We compare our results with baseline TF-IDF results which as expected our model performs a lot better than baseline models. We also compare our model with other variants of BERT specifically: BERT-GRU, BERT-CRF and ALBERT [48] observing the F1 scores on the development set. We observe no significant difference in the performance of these models except using ALBERT which performs significantly lower. However, we also observe that using BERT-base uncased is quite robust to overfitting on comparing with other variants.

We also observe the impact of fine-tuning BERT for our use-case and impact of it on the final performance. We, use BERT to calculate the token-level representations while

keeping the other parameters of the BERT component constant. We observe that the pre-trained BERT representation was far from the fine tuned results with almost 25 - 35 % improvement across all variants of BERT and approximately 27% improvement on our best performing BERT-base uncased model.

The general purpose representations are far from satisfactory and task-specific fine-tuning was essential to exploit the strengths of BERT and perform better on downstream tasks improving the overall performance.

V. CONCLUSION AND FUTURE WORK

At the current work, we study the BERT effectiveness as a component being embedded on the Keyword extraction task from Job Descriptions. Precisely, we search coupling BERT as component being embedded to different other techniques to build an end-to-end keyword extractor. The obtained results exhibit BERT-based models' superiority in identifying aspect-based keywords along their robustness to over-fitting. We also build an API allowing this to be easily used or integrated into organizations and even be used by HRs and administrators.

The future work includes using the same model making minor changes to the downstream models according to the task use it for resume screening, automatic keyword adding for SEO or summarizing corporate text.

CONFLICT OF INTEREST

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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⁵<https://www.tensorflow.org/tfrc>

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